Fuzzy Knowledge Based Expert System for Prediction of Color Strength of Cotton Knitted Fabrics

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ABSTRACT
The present study is intended to develop an intelligent model for the prediction of color strength of cotton knitted fabrics using fuzzy knowledge based expert system (FKBES). The factors chosen for developing the prediction model are dye concentration, dyeing time and process temperature. Besides, such factors are nonlinear and have mutual interactions among them; so it is not easy to create an exact correlation between the inputs variables and color strength using mathematical or statistical methods. In contrast, artificial neural network and neural-fuzzy models require massive amounts of experimental data for model parameters optimization which are challenging to collect from the dyeing industries. In this context, fuzzy knowledge based expert system is the most efficient modeling tool which performs exceptionally well in a non-linear complex domain with lowest amount of trial data like human experts. In this study, laboratory scale experiments were conducted for three types of cotton knitted fabrics to verify the developed fuzzy model. It was found that actual and predicted values of color strength of the knitted fabrics were in good agreement with each other with less than 5% absolute error.

Keywords: FKBES; Color strength; Cotton; Knitted Fabric; Dyeing; Modeling

INTRODUCTION
Dyeing is the most complex process other than the weaving and spinning in the textile manufacturing which combines with science of chemistry, physics, mechanics, physical chemistry, fluid mechanics and thermodynamics [1-2].The quality of dyed fabrics is considered a big issue in the today's textile and apparel market. The demand of knitted fabrics especially dyed knitted fabrics is increasing rapidly due to their exclusive quality characteristics like elasticity, drape, wrinkle resistance, comfort, softness and easy-care properties over woven fabrics. Due to their unique quality characteristics compared to woven fabrics, in recent times, knitted fabrics are typically preferred for apparel wears such as T-shirts, shirts, sweaters, blouses, underwear, casual wear, active wear and sportswear [3-4]. The present dyeing industry is facing tremendous challenges in the global textile and apparel market due to the shorter life cycle of product development, increasing product diversity, high demand of product quality and above all product costing. However, traditional dyeing process depends on trial and error which is time consuming, less efficient and produces fabrics of inferior quality. Moreover, dyeing process automation is developing gradually due to the complexity of the processes [2]. The color strength is one of the most important chemical properties to the consumers among all dyed knitted fabrics quality characteristics. In the dyeing process, however, many inside and outside factors affecting the fabrics color strength are the dye concentration, dyeing time, temperature, alkali concentration, salt concentration, liquor ratio etc. [5, 6]. In case of cotton knitted fabrics when dyeing with reactive dyes in exhaust dyeing, the important key factors affecting color strength are dye concentration, dyeing time and process temperature. Moreover, the factors affecting the color strength are very non-linear and have mutual interactions between them. As a consequence, it is very difficult to create an efficient correlation between the input variables and the color strength using mathematical models or statistical models [7, 8].

The literature review revealed a few numbers of predictive models such as mathematical models, statistical regression models, artificial neural network (ANN) models and adaptive neural-fuzzy models (ANFIS) to predict the fabrics quality characteristics like color strength, fastness, levelness, pilling resistance, bursting strength etc. [7-9]. A summary of these works have been reported here.

The mathematical models developed by Zaverah, Hamadani and Tavanai [5] and Fazeli, Tavanai and Hamadani [10] in the related study have been based on the fundamental theories of basic sciences and developed on the origin of hypothesis or sweeping statements. Hence, the prediction accuracy of mathematical models is not very encouraging. The statistical regression models on the other hand, founded by Kuo and Pietras [11], Kuo and Fang [12] and Zeydan and Toga [6] have been applied in the related research. However, prior assessment of type of functional relationship between inputs and outputs is important to develop a statistical regression model. Moreover, statistical regression models are unable to capture the non-linear relationship between inputs and outputs [8].

In recent years, the advent of artificial intelligence has received lots of interest from researchers in the related research investigation. The ANN models developed by Elemen, Kumbasar and Yapar [13], Khataee et al. [14], and ANFIS models developed by Shams-Nateri [15] in the field are related to this research. However, ANN models and adaptive neural-fuzzy models need large amounts of noisy input-output data for model parameters optimization, which are challenging, labor intensive and time consuming process to collect from the dyeing industries. Further, ANN and ANFIS models work as black box and there is no precise amplification of the nature of non-linearity between input-outputs. Therefore, it has been observed from the published literature that predicting color strength using mathematical models, statistical models, ANN models and ANFIS models is uncertain and sometimes complicated work [7-8]. As a result, there is a need for more competent, sound and simple system that can be engaged in modeling such a multifaceted array of process mechanics.

In this background, fuzzy knowledge based expert system is the most efficient modeling tool rather than the conventional, ANN and ANFIS models as fuzzy logic performs outstandingly better as well as it can link the multiple inputs to a single output in a non-linear complex fields with least amounts of experimental data [8, 16-17]. In addition, some lacunas of ANN, ANFIS, statistical regression and mathematical modeling can be overcome by fuzzy logic which can effectively interpret the knowledge of a dyer/dyeing engineer into a set of expert system rules. Unlike statistical regression models, fuzzy system needs no information or prior assessment of any mathematical models in advance. Moreover, fuzzy system does not require huge amounts input-output data for model parameter optimization unlike ANN and ANFIS models. A fuzzy logic model is comparatively easier to apply than others and gives better explanation of the nature of non-linearity among the input and output variables. Besides, fuzzy system is used to resolve the problems in which descriptions of behavior and observations are imprecise, vague and uncertain. The term fuzzy refers to the circumstances where there are well-defined boundaries or explanation for the set of activities. For instance, in textile dyeing industries, a dyer/dyeing engineer often uses terms such as high or low, strong or weak, for assessing the knit dyed fabrics qualities such as color strength, color fastness, color levelness etc. [8].

A few numbers of research investigations by using fuzzy logic approach related to this study have been reported as follows. Jahmeerbacusa et al. [18] developed fuzzy control method for controlling pH in exhaust dyeing to achieve optimum color yield. Hung and Yu [7] presented a fuzzy controller for controlling dye concentration, pH and temperature in cotton fabric dyeing with direct dye to achieve expected color shade and even dyed product quality. Smith and Lu [19] proposed fuzzy logic model for controlling dyeing process in batch dyeing of cotton fabric with reactive dye to achieve desired color shade. Nasri and Berlic [20] discovered evolutionary fuzzy system to model the color yield in polyester dyeing with disperse dye. Tavanai et al. [21] applied fuzzy regression approach to model color yield in polyester dyeing with disperse dye as a function of dye concentration, time and temperature.

The main purpose of this work is to construct a fuzzy knowledge based intelligent model for predicting the color strength of cotton knitted fabrics as a function of dye concentration, dyeing time and dyeing process temperature which has not so far been reported in the published literature. Moreover, this fuzzy prediction model can be applied as a decision making support tool for dyeing engineer to select and adjust dyeing process parameters to achieve desired fabric color strength before starting dyeing process.

MATERIALS AND METHODS

Materials and Equipment

In this experimentation, three types of cotton knitted bleached fabrics with 190 GSM such as 95% cotton with 5% lycra single jersey, 100% cotton 1x1 rib and 100% cotton pique were used for preparing dyed samples. Sodium carbonate (laboratory grade) was used as alkali and glauber salt was used as electrolyte. Remazol Blue RR from Dystar Germany was used as dye. A Laboratory dyeing machine (Brand: Ugolini) and UV Visible spectrophotometer (Brand: Data Color 650 TM) were used in the investigation.

Methods

All bleached cotton knitted fabrics samples (each 5gm) were dyed using exhaust dyeing methods with Remazol Blue RR reactive dyes in a laboratory dyeing machine according to a set of values for dye concentration (%), salt concentration (g/l, alkali concentration (g/l), dyeing time (min), process temperature (0°C) and material: liquor ratio as shown in *Table I*. Commonly, dye concentration, dyeing time and process temperature are the most important factors affecting the color strength of cotton/lycra blended knitted fabrics. After dyeing all the samples were cold rinsed and hot washed at 90°C for 10 minutes. Then, the samples were dried and conditioned for 2 hours at (65±2) % relative humidity and (20±2) $^{\circ}$C temperature. After conditioning, reflectance values of all dyed samples were measured using the spectrophotometer Data Color 650 TM, in a visible region with wavelength ranges of 550 nm, 600 nm and 650 nm and average of three reflectance values for each samples are taken. Finally, the color strength (K/S) was calculated using Kubelka- Munk equation [22].

$$\frac{K}{S}=\frac{(1-R)^2}{2R} \tag{1}$$

where K is the light absorption coefficient, S is the light scattering coefficient and R is the reflectance of dyed fabric.

TABLE I. Dyeing conditions.

Process parameters	Values				
Dye concentration (% o.w.f)	0.5	2.5	4.5	5.5	7
Time (min)	40	50	60	70	
Temperature ($^{\circ}$C)	50	60	70		
Salt concentration(g/l)	45				
Alkali concentration(g/l)	12				
Material: Liquor ratio	1 :10				

DEVELOPMENTOFFUZZYEXPERTSYSTEM

Structure of Fuzzy Expert System

The fuzzy expert system is an artificial intelligence derived from fuzzy set theory, which is a branch of mathematics developed by Zadeh in 1965 [23]. Today, the fuzzy-logic expert system is one of the most successful systems, which focus on several research investigations by mathematicians, scientists and engineers worldwide [24].

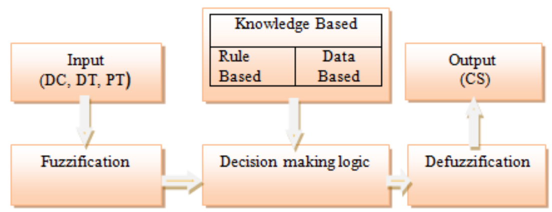

FIGURE 1. Basic configuration of fuzzy logic system [24-26].

Figure 1 shows the basic configuration of a fuzzy logic expert system, which comprises four principal components [24-26]. The four principal components are as follows:

(i) **Fuzzification interfaces**-Fuzzification is the first block inside the fuzzy expert system (FES). The first task in fuzzification interfaces is the selection of input and output variables. After that all input and output numeric variables have to be defined in linguistic terms such as low, medium, high and so on. Subsequently, membership functions for all input and output variables have to be formed. The central concept of fuzzy set theory is membership functions, which represent numerically to what degree an element belongs to a set. A membership function is typical a curve that converts the crisp numerical value of input variable into the fuzzy number within a range from 0 to 1, representing the belongingness of the input to a fuzzy set. There are different forms of membership functions such as triangle, trapezoid, and Gaussian functions. Among these the triangle membership function is the simplest and most often used which is defined as follows:

$$\mu_A(x)=\left\{\begin{array}{ll}\dfrac{x-L}{m-L}; & L\le x\le m\\ \dfrac{R-x}{R-m}; & m\le x\le R\\ 0; & otherwise\end{array}\right\} \tag{2}$$

where m is the most promising value, L and R are the left and right spread (The smallest and largest value that x can take).

The selection of membership functions and their formations is based on system knowledge, expert's appraisals, and experimental conditions. Basically, a small number of parameters and more membership functions provide greater accuracy when using a fuzzy model. However, more membership functions require more fuzzy rules, which increase the complexity of the system [8, 16-17, 24-26].

(ii)**Knowledge base** **–**The second import task of fuzzy modeling is the rule base formation. Moreover, fuzzy rules are the heart of the fuzzy expert system which determines the relationship between input-output of the model**.** This performs as a source to the decision making logic. Moreover, it consists of a data base and a rule base. In the fuzzy knowledge base system, knowledge is represented by if-then rules. Fuzzy rules consist of two parts: an antecedent part stating conditions on the input variables and a consequent part describing the corresponding values of output variables [7-8, 24-26]. For instance, in the case of three inputs P, Q, and R, and one output Z, which have the linguistic variables of very low, medium, and low medium for P, Q and R respectively and medium for Z, then development of fuzzy inference rules can be demonstrated as follows:

If *P* is very low and *Q* is medium, and *R* is low medium then *Z* is medium.

(iii) **Decision making logic**–The decision making logic is the central processing unit of the fuzzy logic system just like computer. It plays a central role in a fuzzy logic model due to its ability to create human decision making and deduce fuzzy control actions as per the information provided by the fuzzification module by applying knowledge about how to control best the process. Most commonly, Mamdani max-min fuzzy inference mechanism is used because it assures a linear interpolation of the output between the rules. For instance, in case of tree-inputs and single-output fuzzy inference system, it can be shown (*Figure. 2*) as below.

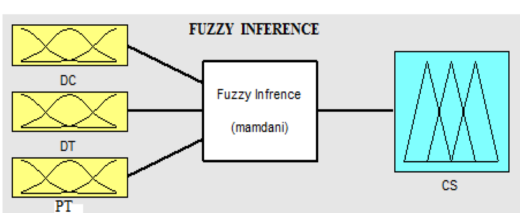

FIGURE 2. Fuzzy inference mechanisms (Mamdani).

where, *DC* (Dye concentration), *DT* (Dyeing time) and *PT* (Dyeing process temperature) are inputs side and *CS* (Color strength) is output side [17, 25].

(iv) **Defuzzification interface**–The conversion of a fuzzy set to a single crisp output on which action can be taken is called defuzzification. The defuzzification interface combines the conclusions reached by the decision making logic and converts the fuzzy output into precise crisp numeric value as control actions. There are several methods of defuzzification such as centroid, center of sum, mean of maxima and left-right maxima. Most commonly, center of gravity (centroid) defuzzification method is used, since this operator assures a linear interpolation of the output between the rules. In this stage, the output membership values are multiplied by their corresponding singleton values and then are divided by sum of the membership values to calculate non-fuzzy value *z* as follows:

$$z = \frac{\sum_{i=1}^{n} \mu_i \left(b_i \right)}{\sum_{i=1}^{n} \mu_i} \tag{3}$$

where, b_i is the position of the singleton in the i^{th} universe, and $\mu_{(i)}$ is equal to the firing strength of truth values of rule *i* [8, 17, 24-25].

Implementation of Fuzzy Expert System

In this investigation, three dyeing process parameters namely dye concentration (DC), dyeing time (DT) and process temperature (PT) have been used as input variables and color strength (CS) of the dyed fabrics as the output variable. These process parameters have been selected since they influence the color strength significantly. For fuzzification, six possible linguistic variables namely very low (VL), low (L), medium (M), medium high (MH), high (H) and very high (VH) were chosen for the input variable DT, four possible linguistic variables namely very low (VL), low (L), medium (M) and high (H) was used for the input variable DT and three possible linguistic variables namely low (L), medium (M) and high (H) was used for the input variable PT. The values were specified in such a way that they were equally spaced and covered the whole input space. In this study, six membership functions for DC, four membership functions for DT and three membership functions for PT have been selected based on system knowledge, expert's appraisals, and experimental conditions and arbitrary choice. From previous experience, it has been found that dye concentration has the most effect on the color strength compared to dyeing time and process temperature, hence six membership functions were chosen for DC. Seven linguistic variables, namely very low (VL), low (L), low medium (LM), medium (M), high medium (HM), high (H) and very high (VH), were considered for the output variable CS, so that the expert system could map small changes in color strength with changes in the input variables. In the present study triangular shaped membership functions have been used for both input and output variables due to their accuracy [18]. In this study, a Mamdani max-min inference approach and the center of gravity defuzzification method have been used since these operators assure a linear interpolation of the output between the rules. The units for the input and output variables are: DC (%), DT (min), PT (^{0}C) and CS (dimension less). For the input and output parameters, a fuzzy associated memory was created as regulation rules based on expert knowledge and previous experience. A total of 72 rules were formed. Some rules are shown in *Table II.*

TABLE II. Fuzzy inference rules.

Rules	Input variables			Output variables
	DC	*DT*	*PT*	*CS*
1	VL	VL	L	VL
-----	-----	-----	-----	-----
2	L	VL	L	L
-----	-----	-----	-----	-----
16	MH	M	L	M
-----	-----	-----	-----	-----
18	H	M	L	MH
-----	-----	-----	-----	-----
36	M	M	H	H
-----	-----	-----	-----	-----
72	H	H	H	VH

In *Table II*, column 2, 3, 4 are used for input variables DC, DT and PT respectively and column 5 is used for output variable CS. Two examples have been illustrated hereunder how the values of last column of fuzzy inference rules are determined.

Rule 1: If input dye concentration (DC) is very low (VL), and dyeing time (DT) is very low (VL), and dyeing process temperature (PT) is low (L), then color strength (CS) is very low (VL).

Rule 36: If input dye concentration (DC) is medium (M), and dyeing time (DT) is medium (M), and dyeing process temperature (PT) is high (H), then output color strength (CS) is high (H).

There is a level of membership for each linguistic word that applies to that input variable. Fuzzifications of the used factors are made by aid follows functions.

$$DC(i_1) = \begin{Bmatrix} i_1; & 0.5 \le i_1 \le 7 \\ 0; & otherwise \end{Bmatrix} \quad (4)$$

$$DT(i_2) = \begin{Bmatrix} i_2; & 40 \le i_2 \le 70 \\ 0; & otherwise \end{Bmatrix} \quad (5)$$

$$PT(i_3) = \begin{Bmatrix} i_3; & 50 \le i_3 \le 70 \\ 0; & otherwise \end{Bmatrix} \quad (6)$$

$$CS(o_1) = \begin{Bmatrix} o_1; & 1 \le o_1 \le 22 \\ 0; & otherwise \end{Bmatrix} \quad (7)$$

where i_1, i_2 and i_3 *are the* first (*DC*), second (DT) and third (PT) input variables respectively and o_1 is the output variable (CS) shown in Eq. (4) to Eq. (7). Prototype triangular fuzzy sets for the fuzzy variables, namely, DC, DT, PT and CS are set up using MATLAB FUZZY Toolbox (version 7.0). The membership values obtained from the above formula are shown in the *Figure 3* through *Figure 6*.

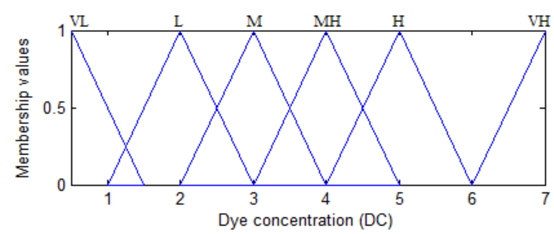

FIGURE 3. Membership functions of input variable DC.

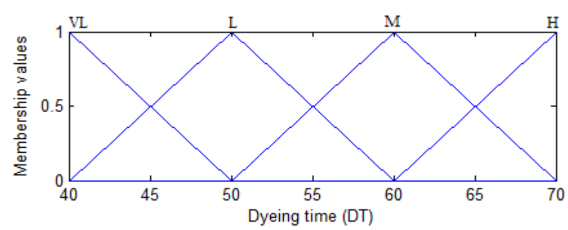

FIGURE 4. Membership functions of input variable DT.

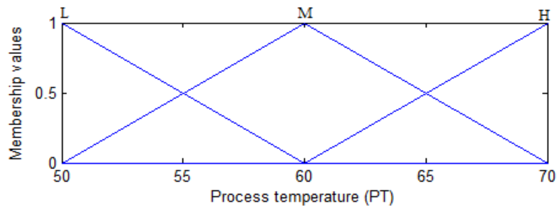

FIGURE 5. Membership functions of input variable PT.

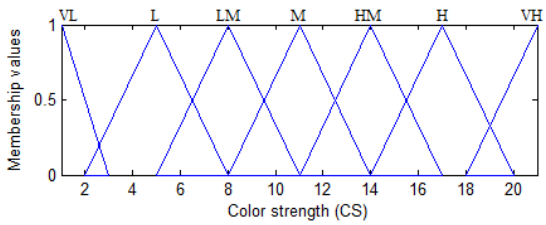

FIGURE 6. Membership functions of output variable CS.

To demonstrate the fuzzification process, linguistic expressions and membership functions of dye concentration (DC), dyeing time (DT), and dyeing process temperature (PT) obtained from the developed rules and above formula (Eq. (4) to Eq. (7)) are presented as follows:

$$\mu_{HM}(DC)=\begin{cases}\dfrac{i_1-3}{4-3}; & 3\le i_1\le 4\\ \dfrac{5-i_1}{5-4}; & 4\le i_1\le 5\\ 0; & i_1\ge 5\end{cases} \tag{8}$$

$$\mu_{HM}(DC)=\{0/3+0.5/3.5+.....+1/4+0.5/4.5+....+0/5\}$$

$$\mu_{H}(DC)=\begin{cases}\dfrac{i_1-4}{5-4}; & 4\le i_1\le 5\\ \dfrac{6-i_1}{6-5}; & 5\le i_1\le 6\\ 0; & i_1\ge 6\end{cases} \tag{9}$$

$$\mu_{H}(DC)=\{0/4+0.5/4.5+...+1/5+0.5/5.5+...+0/6\}$$

$$\mu_{M}(DT)=\begin{cases}\dfrac{i_2-50}{60-50}; & 50\le i_2\le 60\\ \dfrac{70-i_2}{70-60}; & 60\le i_2\le 70\\ 0; & i_2\ge 70\end{cases} \tag{10}$$

$$\mu_{M}(DT)=\{0/50+0.5/55+...1/60+0.5/65+...+0/70\}$$

$$\mu_{L}(PT)=\begin{cases}1\ ; & 50\ge i_3\\ \dfrac{60-i_3}{60-50}; & 50\le i_3\le 60\\ 0; & i_3\ge 60\end{cases} \tag{11}$$

$$\mu_{L}(PT)=\{1/50+........+0.5/55+......+0/60\}$$

In defuzzification stage, truth degrees (μ) of the rules are calculated for each rule by aid of the min and then by taking max between working rules. To comprehend fuzzification, an example is considered. For crisp input linguistic expressions and membership functions of other parameters could be calculated. In defuzzification stage, truth degrees (μ) of the rules are calculated for each rule by aid of the min and then by taking max between working rules. To comprehend fuzzification, an example is considered. For crisp input DC=4.5%, DT=60 min and PT=50°C, the rules 16 and 18 are fired. The firing strength (truth values) α of the two rules are obtained as:

$$\alpha_{16}=\min\{(\mu_{HM}(DC),\mu_{M}(DT)),\mu_{L}(PT)\}=\min((0.5,1),1)=0.5$$
$$\alpha_{18}=\min\{(\mu_{H}(DC),\mu_{M}(DT)),\mu_{L}(PT)\}=\min((0.5,1),1)=0.5$$

Consequently, the membership functions for the conclusion reached by rule (16) and (18) are obtained as follows.

$$\mu_{16}(CS)=\min\{0.5,\mu_{M}(CS)\}$$
$$\mu_{18}(CS)=\min\{0.5,\mu_{MH}(CS)\}$$

Rajasekaran and Vijayalakshmi [27] have mentioned that in many circumstances, for a system whose output is fuzzy, it can be simpler to obtain a crisp decision if output is represented as a single scalar quantity. Using Eq. (3) with *Figure 6* and *Table II*, the crisp output of CS is obtained as 12.5.

Statistical Methods for Comparison

The prediction ability of the developed system has been investigated according to mathematical and statistical methods. In order to establish the relative error (ε) of formation, the following equation is used:

$$\varepsilon=\sum_{i=1}^{n}\left|\frac{y_i-\hat{y}_i}{y_i}\right|\frac{100\%}{n} \tag{13}$$

In addition, goodness of fit (η) of the predicted system is calculated as follows.

$$\eta = \sqrt{1 - \frac{\sum_{i=1}^{n}\left(y_i - \hat{y}_i\right)^2}{\sum_{i=1}^{n}\left(y_i - \bar{y}\right)^2}} \qquad (14)$$

where n is the number of observations, y_i is the measured value, $\hat{y}_i$ is the predicted value, and $\bar{y}$ is the mean of measured (actual) value. The relative error provides the difference between the predicted and measured values and it is necessary to attain zero. The goodness of fit also provides the ability of the developed system and its highest value is 1[17].

RESULTS AND DISCUSSION

Operation of the Fuzzy Logic Prediction Model

Figure 7 graphically shows the operation of the developed fuzzy expert prediction model with an example. For simple demonstration, out of seventy two rules only one fuzzy rule has been depicted in the figure. According to this rule, if dye concentration is high, dyeing time is medium and dyeing process temperature is low then output color strength will be high. For instance, if DC is 4.5%, DT is 60 min and PT is 50°C, then all seventy two fuzzy rules are evaluated simultaneously to determine the fuzzy output color strength (CS), which are 12.5 as shown in *Figure 7*. Using MATLAB (version 7.0) the fuzzy control surfaces were developed as shown in *Figure 8* through *Figure 10.* It can serve as a visual depiction of how the fuzzy logic expert system operates dynamically over time. The pictures show the mesh plot for the above example cases, showing the relationship between dye concentrations (DC), dyeing time (DT) and dyeing process temperature (PT) on the input side and color strength (CS) on the output side.

Figure 8 through *Figure 10* show that each of the surfaces represents in a compact way all the information in the fuzzy logic system. In addition, the images simply represent the range of possible defuzzified values for all possible inputs DC, DT and PT. The surface plots shown in *Figure 8* through *Figure 10* depict the impact of dye concentration, dyeing time and process temperature on the color strength.

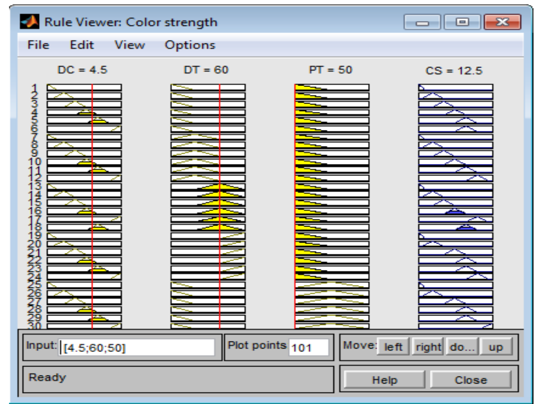

FIGURE 7. Rule viewer of the fuzzy inferring system.

Figure 8 and Figure 11 demonstrate that color strength increases with the increasing dye concentration and dyeing time and vice versa. Color strength increases slowly with the increasing in dyeing time. On the contrary, color strength rises drastically with the increases in dye concentration. Approximately, color strength (CS) increases 6% with an increase of 25% dyeing time while color strength (CS) increases 84% with an increase of 80 % in dye concentration due to more exhaustion and fixation of dyes.

A similar pattern has been observed for the dye concentration (DC) and process temperature (PT) also on the color strength as shown in *Figure 9 and Figure 12*. These figures show that the color strength increases approximately 25% when process temperature increases (20%) from 50^0C to 60°C but it decreases (5%) when process temperature increases from 60°C to 70°C. at dye concentration from 2.5% to 4.5%. The reason for a decrease in color strength within a certain dye concentration and process temperature is probably due to the hydrolysis of dyes at higher temperature. Conversely, color strength increases rapidly with increasing dye concentration. Approximately, color strength increases 80% with an increase of 80% in dye concentration due to more exhaustion and fixation of dyes.

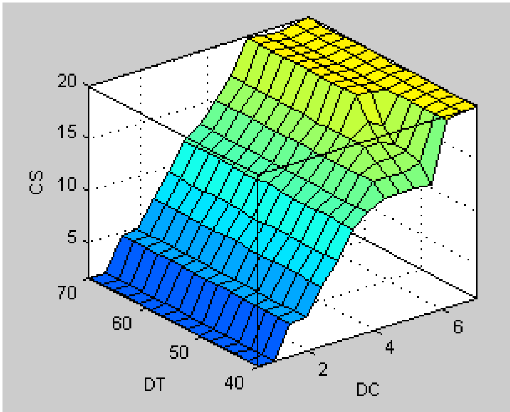

FIGURE 8. Control surfaces of the fuzzy inferring system for color strength at 60^0C PT.

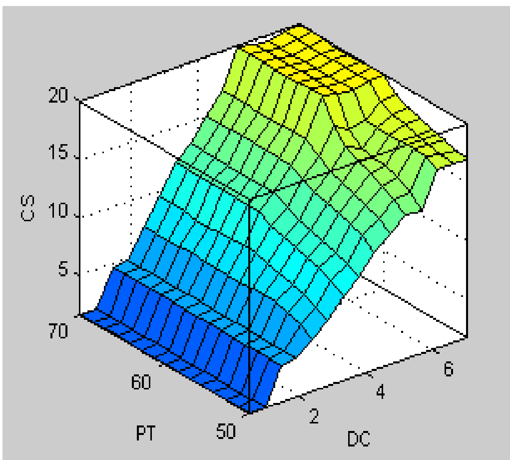

FIGURE 9. Control surfaces of the fuzzy inferring system for color strength at 60 min DT.

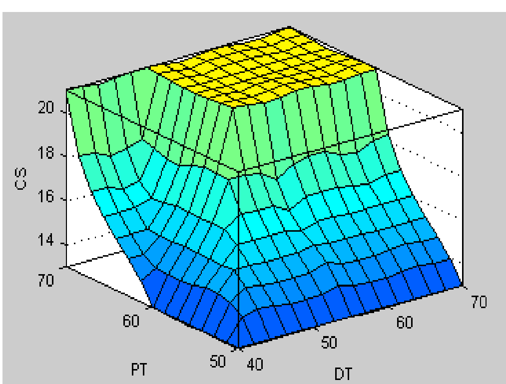

FIGURE 10. Control surfaces of the fuzzy inferring system for color strength at 4.5% DC.

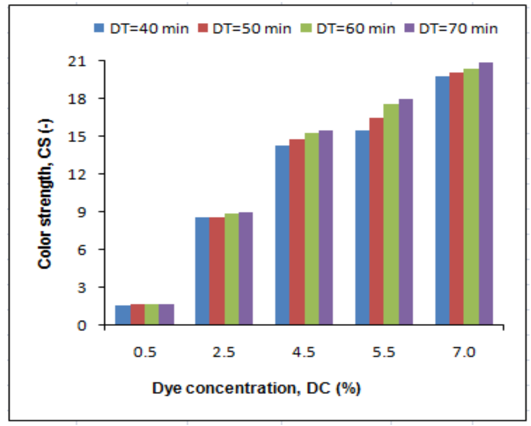

FIGURE 11. Effect of dye concentration and dyeing time on color strength at 60^0C PT.

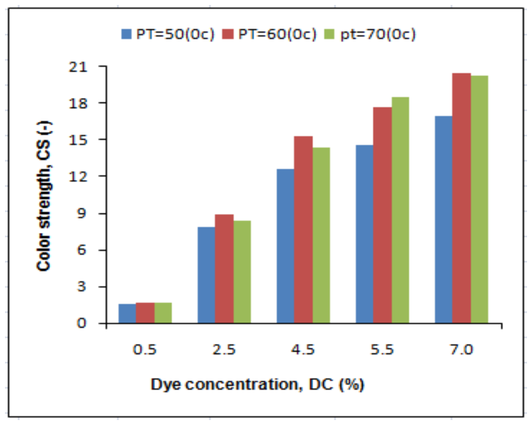

FIGURE 12. Effect of dye concentration and dyeing process temperature on color strength at 60 min DT.

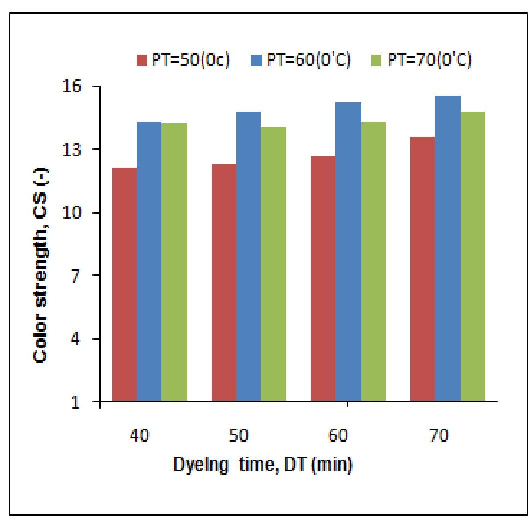

FIGURE 13. Effect of dyeing time and dyeing process temperature on color strength at 4.5% DC.

From *Figure 10 and Figure 13*, it has been observed similar phenomenon for dyeing process temperature on the color strength as *Figure 9 and Figure 12*. It has been further observed from *Figure 10 and Figure 13* that color strength increases very slowly (approx. 3%) with increases in dyeing time from 40-70 minutes. Decisively, it can be concluded from this research that dye concentration has the significant effects on color strength in dyeing process rather than dyeing time and dyeing process temperature.

Validation of the Prediction Model

The model developed in this study has been validated by experimental data of three different types of knitted fabrics such as 95% cotton with 5% lycra single jersey, 100% cotton 1x1 rib and 100% cotton pique. Prediction was done using the fuzzy based intelligent model. The comparisons of predicted and actual values of color strength of three different types of knitted fabrics were presented in *Table III*. The correlation between the measured (actual) and predicted values of color strength of different knitted fabrics under different dyeing conditions have been depicted in *Figure 14*, *Figure 15 and Figure 16*. The relationships were significant for all the parameters in different dyeing conditions for three types of knitted fabrics. The mean absolute errors between the predicted and actual values of color strength were found to be 2.69%, 4.30% and 4.02% for single jersey (95% cotton:5% lycra), 100% cotton 1x1 rib and 100% cotton pique fabrics respectively. The absolute errors explained the good agreement between the predicted and actual (experimental) values of color strength of knitted fabric by the developed model. The correlation coefficients (R) from the predicted and actual values of color strength were found to be 0.998 (R^2=0.997), 0.997 (R^2=0.995) and 0.998 (R^2=0.997) for single jersey (95% cotton: 5% lycra), 100% cotton 1x1 rib and 100% cotton pique fabrics respectively, which also described the excellent conformity between the predicted and actual values of color strength of knitted fabrics by the presented model. The results of the mean absolute error and correlation coefficient indicate very strong prediction ability and accuracy of the developed model. Therefore, it shows the reliable results for all three types of knitted fabrics. The fuzzy knowledge based system is in fact one kind of modeling tool which has been used to develop an intelligent model for the prediction of color strength of three types of cotton knitted fabrics. In the present study, DC from 0.5-7%, DT from 40-70 min and PT from 50-70°C were used as input and CS 1-21(dimension less) was used as output for the fuzzy model development.

TABLE III. Predicted and experimental (actual) values of color strength of different knitted fabrics.

No.	Dye concentration (%)	Dyeing time (min)	Dyeing process temperature (^{0}C)	Predicted values of color strength	Single jersey (95/5)		1x1 rib		Pique	
					Actual color strength	Absolute error %	Actual color strength	Absolute error %	Actual color strength	Absolute error %
1	0.5	60	50	1.6	1.59	0.63	1.52	5.26	1.70	5.88
2	2.5	40	70	8	8.37	4.42	8.16	1.96	8.45	5.33
3	2.5	70	70	8	8.39	4.65	8.46	5.44	8.50	5.88
4	4.5	60	50	12.5	12.64	1.11	12.00	4.17	12.70	1.57
5	4.5	40	60	14	14.31	2.17	13.75	1.82	14.60	4.11
6	5.5	40	50	14	13.50	3.70	13.10	6.87	13.70	2.19
7	5.5	60	50	14	14.50	3.45	13.60	2.94	14.70	4.76
8	7	60	70	20.1	20.38	1.37	18.98	5.9	20.60	2.43
Mean Absolute Error (%)					2.69		4.30		4.02	
Correlation coefficient (R)					0.998		0.997		0.998	

After model development, the output color strength is predicted from the MATLAB® fuzzy rule viewer. As a demonstration of fuzzy model prediction, 8 examples have been shown in *Table III*. Two of the examples can be explained as follows:

Example 1: If DC is 0.5%, DT is 60 min and PT is 50°C, then fuzzy output color strength (CS) is predicted to be 1.6 from the MATLAB® fuzzy rule viewer. Validation experimental color strength were found to be 1.59, 1.52 and 1.70 for single jersey, 1x1 rib and pique fabrics respectively, using same dyeing conditions 0.5% dye concentration, 60 min dyeing time and 50°C dyeing process temperature.

Example 8: If DC is 7%, DT is 60 min and PT is 70°C, then fuzzy output color strength (CS) is predicted to be 20.1 by the fuzzy prediction model. In this case, validation experimental color strength were found to be 20.38, 18.98 and 20.60 for single jersey, 1x1 rib and pique fabrics respectively, using same dyeing conditions 7% dye concentration, 60 min dyeing time and 70°C dyeing process temperature. Thus, it can be positively concluded that fuzzy prediction model can contribute to select significant process parameters and their levels for achieving target product quality. Conversely, when there is no model, a dyer/dyeing engineer has to conduct many trials based on the assumption to achieve target product quality.

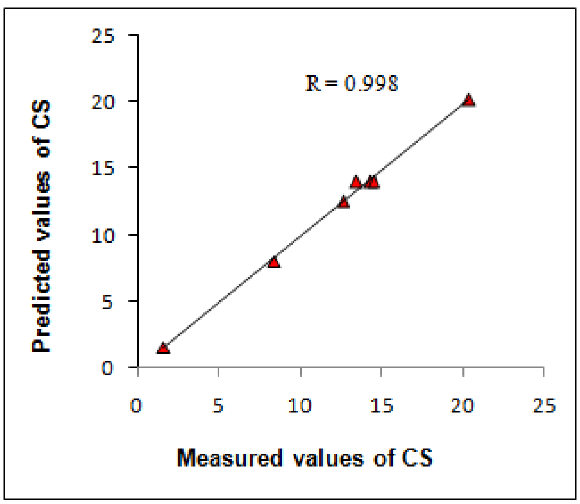

FIGURE 14. Correlation between actual and predicted values of color strength of single jersey fabric.

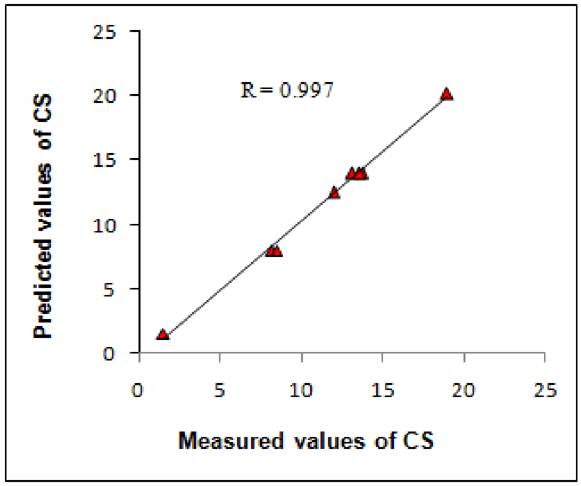

FIGURE 15. Correlation between actual and predicted values of color strength of 1x1 rib fabric.

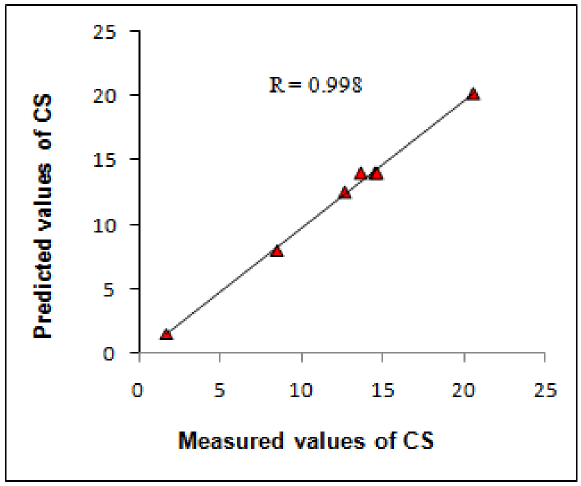

FIGURE 16. Correlation between actual and predicted values of color strength of pique fabric.

CONCLUSION

Prediction of color strength for cotton knitted fabric is necessary in the textile dyeing industries to meet the customers demand. In this study, a fuzzy knowledge based intelligent model has been developed based on dye concentration, dyeing time and process temperature as input variables and color strength of cotton knitted fabric as an output variable. The mean absolute errors from the predicted and actual values of fabrics color strength were found to be 2.69%, 4.3% and 4.02% for single jersey (95% cotton: 5% lycra), 100% cotton 1x1 rib and 100%

cotton pique fabrics respectively. The correlation coefficients (R) were found to be 0.998, 0.997 and 0.998 for single jersey (95% cotton: 5% lycra), 100% cotton 1x1 rib and 100% cotton pique fabrics respectively from the actual and predicted values of fabrics color strength. The results indicate a very strong ability and accuracy of the fuzzy prediction model. Therefore, it can be positively concluded that developed fuzzy intelligent model can be applied as an efficient tool to predict the color strength of cotton knitted fabrics satisfactorily.

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REFERENCES

[1] Hussain T., Wardaman R H and Shamey R, “A knowledge –based expert system for dyeing of cotton, part 1: Design and Development”, *Coloration Technolog*y, 2005, Vol. 121, pp. 53-58.

[2] Shamey M. and Nobbs J. H, "A review automation and computer control in Dyeing machinery", *Advance Colour Science and Technology*, 1998, pp. 46-51.

[3] Bahadir M. C., Bahadir S. K. and Kalaoglu F., “An Artificial Neural Network Model for Prediction of Bursting Strength of Knitted Fabrics”, IMLCS' *2012*, PP.167-170.

[4] Jamshaid H., Hussain T. and Malik Z. A., “Comparison of Regression and Adaptive neuro-fuzzy Models for Predicting the Bursting Strength of Plain Knitted Fabrics”, *Fibers and Polymers*, 2013, Vol.14, No.7, 1203-1207.

[5] Zavareh M., Hamadani A.Z. and Tavanai H., "Application of Central Composite design (CCD) to model color Yield of six diazo direct dyes on cotton fabric". *The Journal of Textile Institute,* 2010, Vol. 101, No. 12, pp. 1068-1074.

[6] Zeydan M. and Toga G., “Reducing variation of Dyeing process in Textile Manufacturing Industry”, *World Academy of Science, Engineering and Technology*, 2011, Vol. 59, pp. 1626-1634.

[7] Huang C.C. and Yu W.H., “Control of dye concentration, pH and temperature in dyeing process”, *Textile Research Journal*, 1999, Vol. 69, pp. 914-918.

[8] Majumdar A. and Ghosh A., “Yarn Strenghth Modeling Using Fuzzy Expert System”, *Journal of Engineered Fibers and Fabrics*, 2008, Vol. 3, No. 4, pp. 61-68.

[9] Asim F., Mahmood M. and Siddiqui M.A.,“Optimization of process parameters for simultaneous fixation of reactive printing and crease resistant finishing using desirability function”, *Journal of Textile and Apparel, Technology and Management*, 2012,Vol. 7, No.3, pp. 1-12.

[10] Fazeli F.,Tavanai H. and Hamadani A. Z., “Application of Taguchi and Full Factorial Experimental Design to Model the color Yeild of cotton Fabtic Dyed with Six Selected Direct Dyes”, *Journal of Engineered Fibers and Fabrics,* 2012, Vol. 7, No.3, pp. 34-42.

[11] Kuo C.C. and Pietras S., “Applying regression analysis to improve dyeing process quality: a case study”, *International Journal Advance Manufacturing Technologies,* 2010, Vol. 49, pp. 357-368.

[12] Kuo C.F.J. and Fang C.C., “Optimization of the Processing Conditions and Prediction of the Quality for Dyeing Nylon and Lycr-Blended Fabrics*”, Fibers and Ploymers*, 2006, Vol.7, No. 4, pp. 344-351.

[13] Elemen S., Kumbasar E. P. A. and Yapar S., “Modeling the adsorption of textile dye on organoclay using an artificial neural network”, *Dyes and Pigments*, 2012, Vol. 95, No. 1, pp. 102-111.

[14] Khataee et al., “Neural network modeling of biotreatment of triphenyl methane dye solution by a green macroalgae”, *Chemical Engineering Research and Design*, 2011, Vol. 89, No. 2, pp. 172-178.

[15] Shams-Nateri, “Estimation of fabric color by camera besed neuro-fuzzy technique”, *Indian journal of Fibre & Textile Resarch*, 2011, Vol. 36, pp.74-80.

[16] Hossain A., Rahman A. and Mohiuddin A. K. M., Fuzzy expert system for controlling swamp terrain intelligent air-cushion tracked vehicle, *International Journal of automotive Technology*, 2011, Vol. 12, No. 5, pp. 745-753.

[17] Carman K., "Prediction of soil compaction under pneumatic tires using a fuzzy logic approach", *Journal of Terramechanics*, 2008, Vol. 45, pp. 103-108.
[18] Jahmeerbacus M.I., Kistamahb N. and Ramgulam R.B., "Fuzzy control of dyebath pH in exhaust dyeing", *Coloration Technology*, 2004, Vol. 120, No. 2, pp. 51–55.
[19] Smith B. and Lu J., "Improving Computer Control of Batch Dyeing Operations", *American Dyestuff Reporter*, September, 1993, pp. 17-36.
[20] Nasri M. and Berlik S.,"Modeling of Polyester Dyeing Using an Evolutionary Fuzzy System", *IFSA-EUSFLAT*, 2009, pp. 1246-1251.
[21] Tavanai H.,Taheri S.M. and Nasiri M.," Modelling of Colour Yield in Polyethylene Terephthalate Dyeing with Statistical and Fuzzy Regression", *Iranian Polymer Journal*, 2005, Vol. 14, No.11, pp. 954-967.
[22] Baumann et al.,"Determination of Relative Colour Strength and Residual Colour Difference by Means ofReflectance Measurements", *Society of Dyers and Colourist*, 1987, Vol. 103, pp. 100-105.
[23] Zadeh L.A., "Fuzzy Sets", *Information and Control*, 1965, Vol. 8, pp. 338-353.
[24] Gopal M., "Digital control and state variable methods: conventional and intelligent control systems", 3rd ed. Singapore: *Tata McGraw-Hill Education Pvt. Ltd*.; 2009.
[25] Hossain A., Rahman A. and Mohiuddin A.K.M., "Fuzzy evaluation for an intelligent air-cushion tracked vehicle performance investigation", *Journal of Terramechanics*, 2012, Vol. 49, pp. 73-80.
[26] Passino K.M. and Yurkovich S., "Fuzzy control", Menlo Park, (USA): *Addison Wesley Longman*, Inc.; 1998.
[27] Rajasekaran S.and Vijayalakshmi Pai GA., "Neural networks, fuzzy logic and genetic algorithms: synthesis and applications", *Prentice-Hall of India Private Limit, New Delhi*, 2007.

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